

# Bias corrections of global models for regional climate simulations of high-impact weather

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**Abstract** All global circulation models (GCMs) suffer from some form of bias, which when used as boundary conditions for regional climate models may impact the simulations, perhaps severely. Here we present a bias correction method that corrects the mean error in the GCM, but retains the six-hourly weather, longer-period climate-variability and climate change from the GCM. We utilize six different bias correction experiments; each correcting different bias components. The impact of the full bias correction and the individual components are examined in relation to tropical cyclones, precipitation and temperature. We show that correcting of all boundary data provides the greatest improvement.

## 1 Introduction

Global circulation models (GCMs) provide the basis of our capacity to simulate, understand and predict climate variability and change. These models are based on established physical laws and have proven fidelity for assessing changes to global quantities (Randall et al. 2007; Anderson et al. 2004; Collins et al. 2004; Déqué et al. 1994; Flato et al. 2013; Pope et al. 2000; Roeckner et al. 2003). However, GCMs typically are of too a coarse resolution to directly infer climatology of high-impact weather at local scales and it is common to downscale over regions of interest using statistical techniques or nested regional

climate models (RCMs). Unfortunately, biases that may be acceptable at global scales can be problematic for these downscaling applications to regional and extreme weather climate scales (e.g. Liang et al. 2008; Ehret et al. 2012; Xu and Yang 2012; Done et al. 2013).

One approach is to apply combined bias-correction and downscaling methods directly to the GCM data in the form of empirical relationships between the large scales and high impact weather (Camargo et al. 2007; Walsh et al. 2007; Bruyère et al. 2012). An obvious shortcoming of this method is that this bias correction is applied independently across time, space and variable, without taking into account feedback mechanisms between atmospheric processes. It is important to also remember that the GCM data were generated at a coarse resolution, where local processes and terrain heterogeneity were not taken into account. It also is possible that statistical downscaling methods developed on past climate might not hold true under climate change conditions.

An alternative, widely-used approach is to nest a RCM within GCM boundary conditions (Laprise et al. 2008; Bender et al. 2010; Knutson et al. 2007, 2008; Walsh et al. 2004; Done et al. 2013). Because of their smaller domain, RCMs can operate at higher resolution than GCMs to enable simulation of much finer scale features, which are required for assessment of many extreme weather phenomena. One shortcoming of this approach is the transmission of GCM biases through the RCM lateral and lower boundaries, which may have a severe impact on the interior climate (e.g. Warner et al. 1997; Done et al. 2013).

One approach to correcting these regional biases is to apply a correction to the RCM output (e.g. Dosio and Paruolo 2011). This approach suffers from the same limitations as the aforementioned statistical bias correction of GCMs and has the additional complication that GCM biases may irretrievably change—or even destroy—the

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high-impact weather signal of interest (Ehret et al. 2012; Done et al. 2013).

An alternative bias-correction approach is to construct boundary conditions from a current climate reanalysis plus a climate change perturbation, a technique known as pseudo-global-warming (Schär et al. 1996; Rasmussen et al. 2011). This approach is simple to apply and takes advantage of the improved ability of GCMs to simulate trends compared to absolute climates (Randall et al. 2007). However, there are substantial disadvantages arising from the inherent assumption of no change in synoptic and climate variability. Biases from current GCM simulations also may change into the future and alias into the imposed climate change perturbation.

A more recent approach takes advantage of the strengths in both the GCMs and RCMs by performing bias correction on the GCM boundary data. Using a common bias-correction method applied to all variables provides more balanced atmospheric conditions to drive the RCM. Variance is free to change into the future (within the resolution constraints of the driving GCM) and the RCM has the freedom to develop its own interior solution within the bias corrected boundary data. A number of variations on this theme have been attempted including; correcting bias in the mean and variance (Xu and Yang 2012), quantile–quantile mapping (Colette et al. 2012), and feature location correction (Levy et al. 2012). White and Toumi (2013) tested both the mean bias correction and quantile–quantile mapping methods, and found that the mean bias correction method is a more reliable and accurate method compared to the quantile–quantile mapping method.

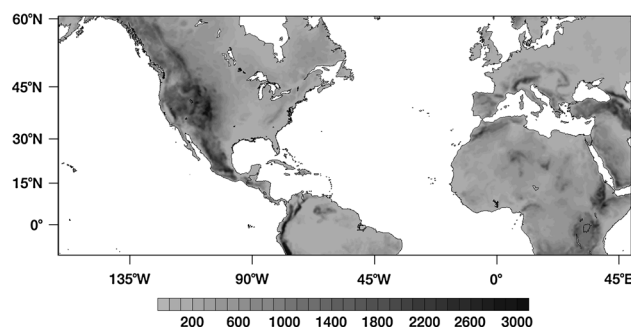
In this study we investigate the applicability of bias correcting the boundaries in RCM simulations of high-impact weather. The environments for Atlantic tropical cyclones and North American summer precipitation and temperatures are used as examples, but the results are applicable to a wide range of weather extremes.

In Sect. 2.2 a bias correction method for GCM boundary conditions is developed that successfully reproduces the statistics of high-impact weather in the regional climate simulation. We then develop physical insight into the role of bias correction for the downscaled regional climate in Sect. 3.2 through analysis of the simulation sensitivity to bias correction of specific variables or sets of variables in the driving data. The results are presented in Sect. 3. Section 4 contains our conclusions.

## 2 Methodology

### 2.1 Models and data

The GCM used here is the Community Climate System Model version 3 (CCSM3; Collins et al. 2006) run at T85



**Fig. 1** Regional domain used for all RCM simulations. Shading represents terrain height (m)

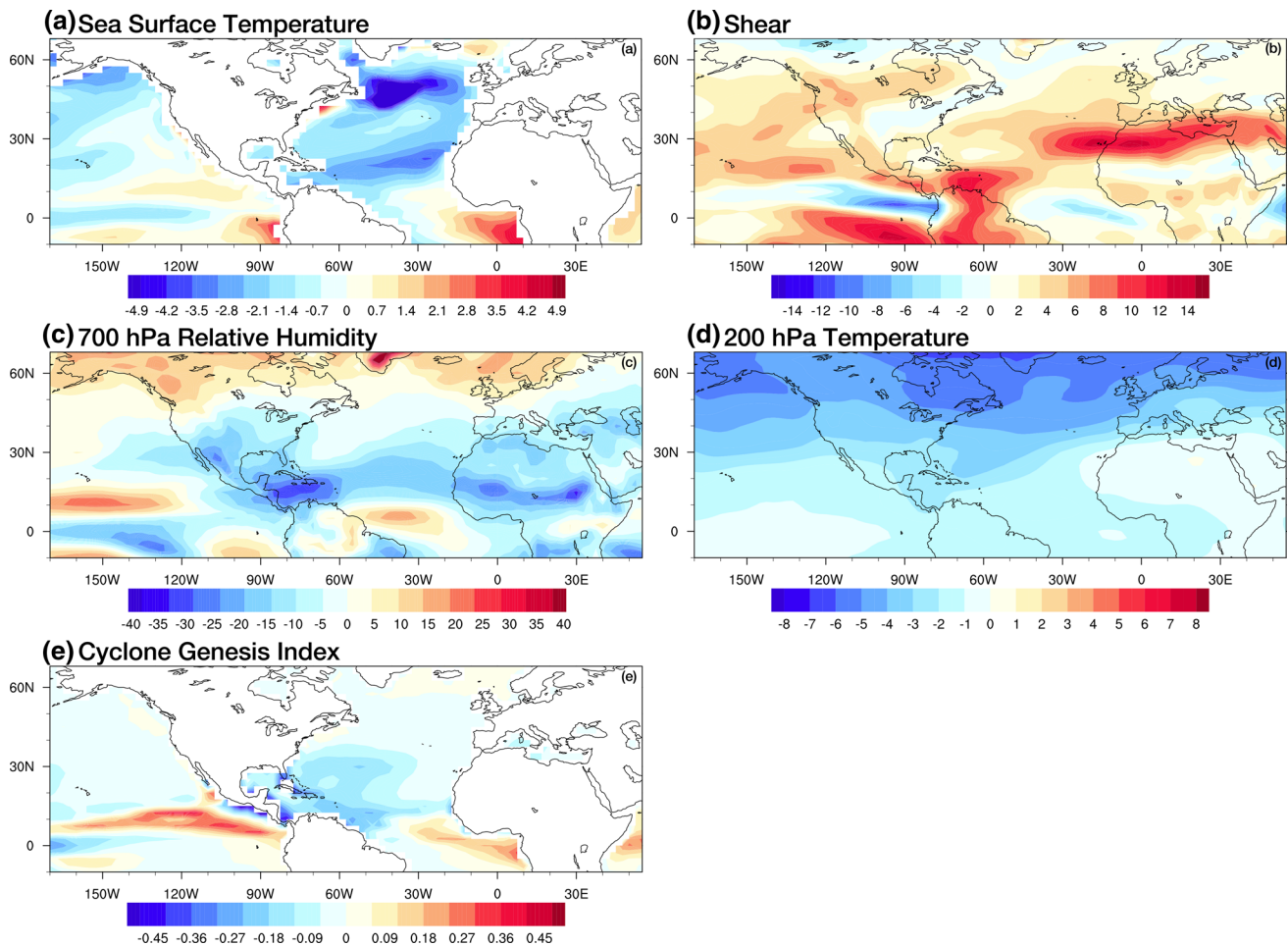
( $\sim 1.4^\circ$  atmosphere and  $1^\circ$  ocean). CCSM3 is a coupled climate model with components representing the atmosphere, ocean, sea ice, and land surface as described in detail in Collins et al. (2006). The simulation was initialized in 1950 and run under twentieth century emissions.

The NCAR Weather Research and Forecasting model (WRF; Skamarock et al. 2008) is nested into CCSM3 for downscaling as the nested regional climate model (NRCM, Done et al. 2013). The WRF model is a fully non-hydrostatic model, and is routinely used for real-time hurricane forecasting (Davis et al. 2008) and regional climate studies (see the discussion in Done et al. 2013). The NRCM domain (Fig. 1) extends from 10S to 60N, and from 160W to 50E. Grid resolution is  $\sim 36$  km with 51 vertical levels. All model simulations used the Kain–Fritsch convective parameterization scheme (Kain 2004), WSM6 microphysics scheme (Hong and Lim 2006), CAM long- and shortwave radiation schemes (Collins et al. 2004), the Yonsei University planetary boundary layer scheme (Hong et al. 2006), and the Noah land surface model (Chen and Dudhia 2001).

The atmospheric reanalysis used to bias correct the CCSM3 data is the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCAR) Reanalysis Project (NNRP, Kalnay et al. 1996). Analysis SST data utilize the merged Hadley Centre and NOAA’s optimum interpolation (OI) SST data set (Hurrell et al. 2008).

### 2.2 Bias correction

Note that here we are using the term bias in the context of systematic errors in the model, as compared to some base ‘truth’ (specifically the NNRP). We also partially consider the ‘bias’ that may arise from sampling from relatively short time periods within a climate that varies on long and short time scales (e.g. Maraun 2012). This is accomplished through our use of a limited set of longer simulations. A related ‘bias’ arising from the essentially nonlinear nature of climate, which means that more than one internal solution may result from the same imposed boundary conditions is the subject of a separate study.



**Fig. 2** 20 year (1975–1994) Aug–Sep–Oct mean bias (CCSM3–NNRP) for **a** Sea Surface Temperature (K), **b** 850–200 hPa Wind Shear ( $\text{ms}^{-1}$ ), **c** 700 hPa Relative Humidity (%), **d** 200 hPa Temperature (K), and **e** Cyclone Genesis Index

The CCSM3 model output contains substantial mean biases compared to NNRP and OI-SST data (Fig. 2). A cold SST bias over the North Atlantic Ocean and a warm SST bias along the west coasts of the Americas (Fig. 2a; Large and Danabasoglu 2006) results in a permanent El Niño-like condition and this drives a high vertical wind-shear bias (defined as the difference in winds between 200 and 850 hPa, Fig. 2b) over the tropical Atlantic through a modified Walker Circulation (e.g. Gray 1984). In addition, the CCSM3 is drier (Fig. 2c), and colder aloft (Fig. 2d) than the NNRP.

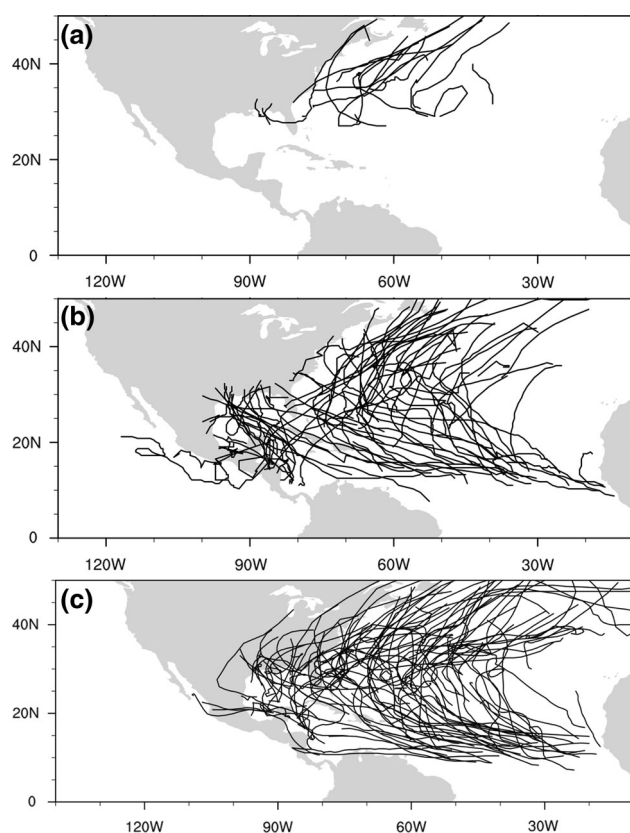
Application of the Cyclone Genesis Index (CGI, Bruyère et al. 2012) indicates a significant low bias over the North Atlantic (Fig. 2e), a result of the combined cool SST and high vertical shear over the development region. This is confirmed when the NRCM is driven with the raw CCSM3 model data with resulting suppression of almost all tropical cyclone development (Fig. 3a) to an average of only 1.5 storms per year, compared to the observed average of  $\sim 9$ –12 (Knapp et al. 2010). The storms that occur also

tend to develop much further poleward than observed (Fig. 3c), away from the regions of high shear and low moisture shown in Fig. 2.

Bias correction of the CCSM3 boundary conditions uses the approach in Holland et al. (2010) (see also Xu and Yang 2012; Done et al. 2013), which can be applied consistently across variables and times. This corrects the mean bias from the GCM, but allows synoptic and climate variability to change and is similar to the approach used in Maraun (2012). Six-hourly GCM data are broken down into a mean seasonally-varying climatological component ( $\overline{GCM}$ ) plus a perturbation term ( $GCM'$ ):

$$GCM = \overline{GCM} + GCM' \quad (1)$$

The mean climatological component is defined over a 20-year base period (to smooth out influence of short-period variations such as El Niño). Twenty years was chosen to avoid inclusion of any significant climate trends though we acknowledge that this may alias some decadal oscillations into the bias correction.



**Fig. 3** Tropical storms generated by the RCM over the 11-year period 1995–2005 when driven by **a** raw CCSM3 data, **b** bias corrected CCSM3 data, **c** and observed TC tracks from an arbitrary 11 year current period

The NNRP reanalysis and OI-SST ( $Obs$ ) is similarly broken down into a seasonally-varying mean climatological component ( $\overline{Obs}$ ) and a six-hourly perturbation term ( $Obs'$ ):

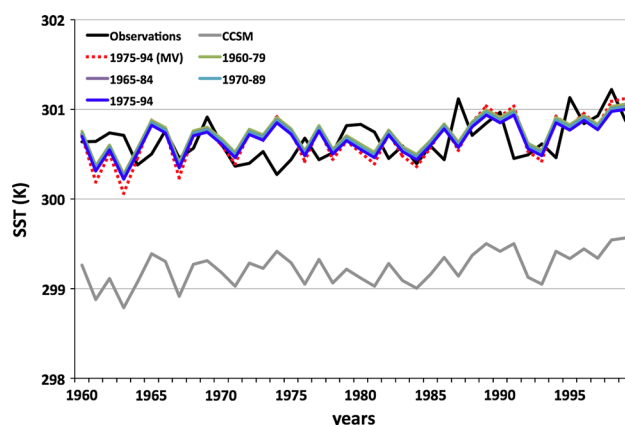
$$Obs = \overline{Obs} + Obs' \quad (2)$$

The bias corrected climate data for the NRCM boundary conditions,  $GCM^*$ , are then constructed by replacing the GCM climatological mean from Eq. 1 with the  $Obs$  mean from Eq. 2:

$$GCM^* = \overline{Obs} + GCM' \quad (3)$$

These bias-corrected climate data thus combine a seasonally-varying climate, as provided by NNRP and OI-SST, with the six-hourly weather from the GCM. This approach also retains the GCM longer-period climate variability and climate change.

Equation 3 is applied to all the variables required to generate surface and lateral boundary conditions for NRCM: zonal and meridional wind, geopotential height, temperature, relative humidity, sea surface temperature and mean sea level pressure.



**Fig. 4** Aug–Sep–Oct mean Sea Surface Temperature over the MDR off the coast of Africa for: observations (*black*); raw CCSM3 (*grey*); mean bias corrected CCSM3 data using different base periods 1960–1979, 1965–1984, 1970–1989, and 1975–1994 (*green*, *purple*, *teal* and *blue*); and mean and variance bias corrected CCSM3 data using the base period 1975–1994 (*dashed red*)

### 3 Results

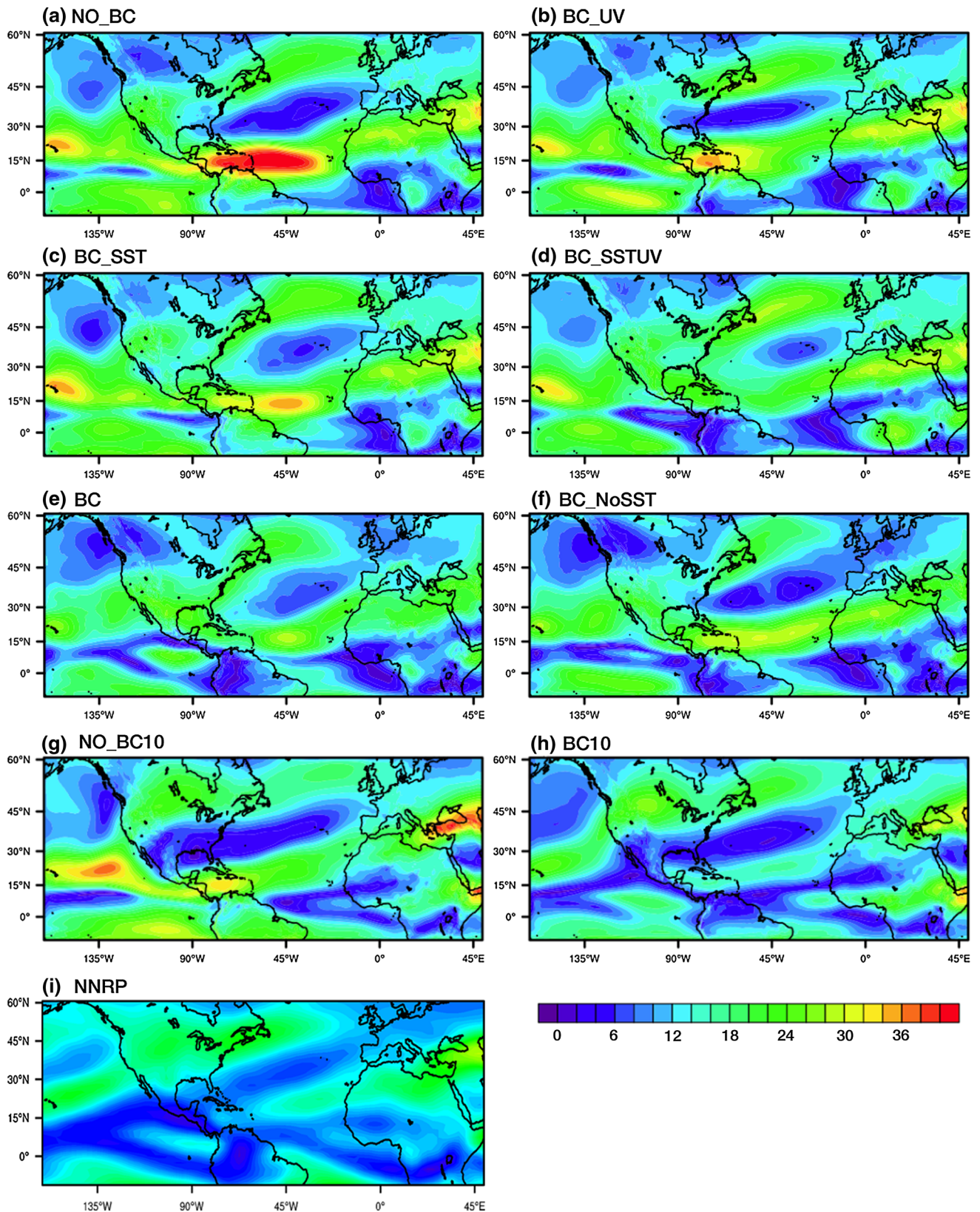
#### 3.1 CCSM bias corrections

Figure 4 illustrates the SST bias-correction changes to the CCSM3 data. Represented in this figure is the average Aug–Sep–Oct (ASO) SST over the hurricane Main Development Region (MDR, 5–20°N; 20–60°W) from observations, together with the raw and bias-corrected CCSM3 simulation. The MDR was chosen as an indicative example because of its importance as an indicator of Atlantic tropical cyclone activity (Bruyère et al. 2012). However, any region—including the entire model domain—together with other variables or time averages could equally well have been chosen. Compared with observations (black line), the CCSM3 raw data (grey line) have a cold bias of almost 2 K. The bias correction procedure brings the revised CCSM3 time series (blue line) up to values within the observed SST error range (*less than 0.1 °C over the North Atlantic*) as specified by Hurrell et al. (2008).

We next examine the sensitivity of the revised climate to the choice of the base period arising from a possible non-stationarity of the bias. Choosing different base periods (1960–1979, 1965–1984, 1970–1989, and 1975–1994) result in nearly identical bias corrections over the entire simulation period (Fig. 4). This increases confidence that the bias will not change substantially in the future. The validity of this assumption is further addressed in the climate projection discussion.

The dashed red line in Fig. 4 shows the affect of including variance bias correction in addition to the mean correction (following the method of Xu and Yang 2012). Clearly, accounting for variance in addition to mean bias

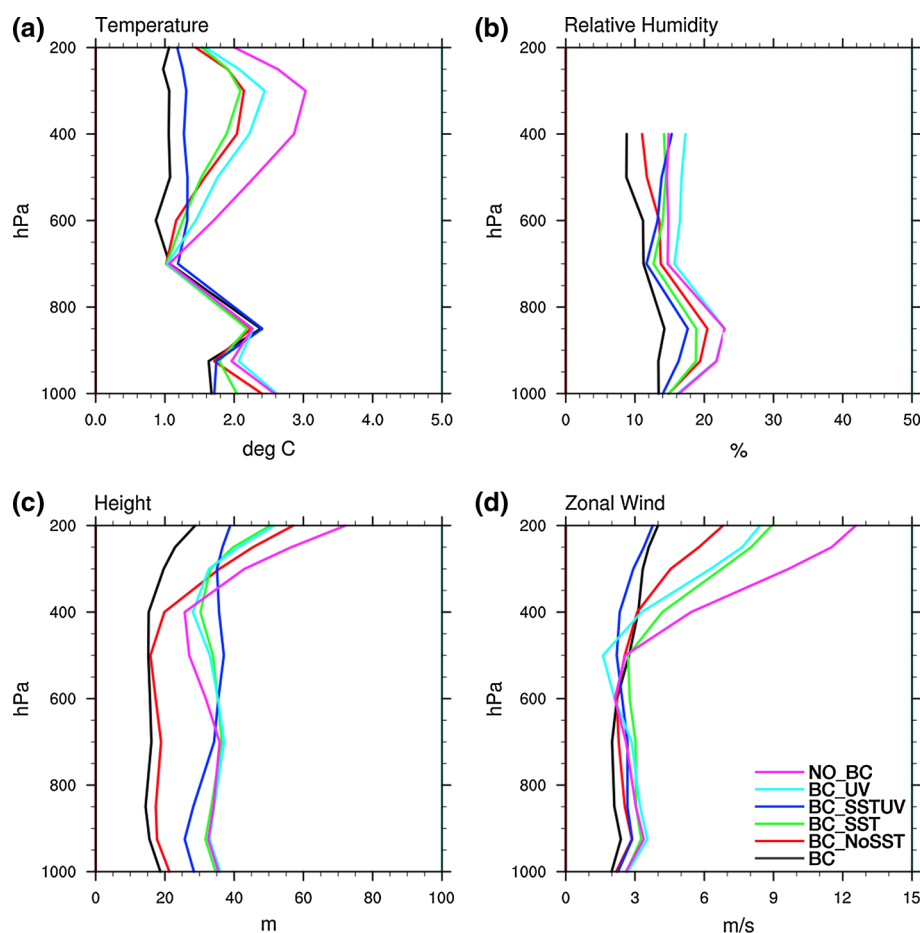




**Fig. 5** ASO mean wind shear (200–850 hPa,  $\text{ms}^{-1}$ ) for cases with bias correction applied to: **a** no variables (NO\_BC), **b** winds (BC\_UV), **c** SST (BC\_SST), **d** winds and SST (BC\_SSTUV), **e** all boundary variables

(BC), **f** all boundary variables excluding SST (BC\_NoSST), **g** no variables for a 10-year simulation (NO\_BC10), **h** all boundary variables for a 10-year simulation (BC10), and **i** a 20-year (1975–1994) NNRP average

**Fig. 6** RSME profiles for **a** temperature (K), **b** relative humidity (%), **c** height (m), and **d** zonal wind ( $\text{ms}^{-1}$ )



makes only a marginal difference. This is supported by the NRCM downscaling with mean bias-only correction. For current climate, the variance in 500 hPa temperature over the MDR is 0.88 for NNRP and 0.62 for the CCSM3 model. Yet, the NRCM with mean bias correction has a variance of 0.96, indicating that it is effectively spinning up realistic internal variance without the need for additional variance bias correction.

### 3.2 NRCM downscaling

Sensitivity to choice of variables used for bias correction is examined using a series of NRCM simulations with the following boundary conditions: raw CCSM3 data (NO\_BC); bias corrected winds only (BC\_UV); bias corrected SST only (BC\_SST); bias correction of both the winds and SST (BC\_SSTUV); all variables excluding SST corrected (BC\_NoSST); and all boundary data corrected (BC). These simulations cover a 7 months period from May 1 to Dec 1, for an arbitrarily chosen year representative of current climate. Note that for the surface only the SST is prescribed, the land is free to evolve in NRCM.

Analysis of these sensitivity runs uses the ASO average large-scale flow, however, since the anomalies in a single

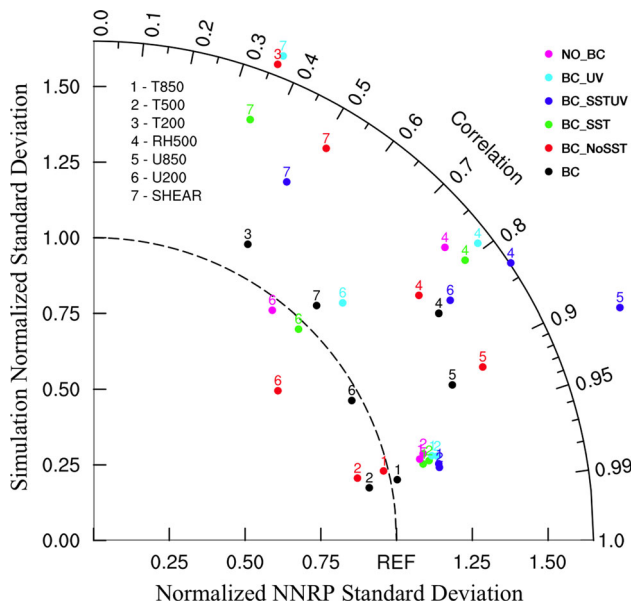
year may not be representative of the anomaly over a longer period, we also compare the NO\_BC and BC cases for a total of 11 years, using the first year as a spin-up year, and years 2–11 for the analysis period. These simulations are referred to as NO\_BC10 and BC10.

#### 3.2.1 Atlantic tropical cyclone environment

Figure 5 depicts the ASO mean wind shear for the six sensitivity simulations. The NO\_BC case (Fig. 5a) has anomalously high shear values (up to  $40 \text{ ms}^{-1}$ ) over the North Atlantic Ocean and especially in the MDR. This strong shear extends all the way to the North American coast and suppresses cyclogenesis to the point that not a single cyclone develops in the basin.

Applying bias corrections to individual or combinations of boundary variables results in the following:

- Winds (BC\_UV, Fig. 5b) or SST (BC\_SST, Fig. 5c) alone both reduce the shear bias substantially. This is expected: correcting the SST bias removes the anomalous Walker circulation that generates the strong vertical shear; applying wind corrections at the boundaries also suppresses this Walker circulation in the regional model.



**Fig. 7** Taylor diagram showing normalized standard deviation and correlations of the indicated simulations and variables compared to NNRP. Colored dots indicate different choices of boundary corrections and numbers different variables averaged over the MDR. To present all the variables on one diagram, the standard deviation of each modeled variable has been normalized to the standard deviation of the observations. A perfect simulation would lie at 1 on the abscissa. (The plot has been scaled for legibility, resulting in some data points being outside the plotting area.)

Notably, although both brought about a similar reduction in shear magnitude, leaving the cold SST in place (BC\_UV) still suppresses all cyclone activity, whereas the warm oceans (BC\_SST) combined with reduced vertical shear generates three cyclones (*not shown*).

- Combining SST and wind corrections (BC\_SSTUV, Fig. 5d) improves the shear values comparable to the sum of the shear improvement through correcting SST and winds independently (Fig. 5b, c). This improvement results in the genesis of five cyclones, some of which form in the MDR.
- All boundary variables (BC; Fig. 5e), produces shear patterns similar to those seen in observations (Fig. 5i), and results in the formation of 7 cyclones in the MDR and the Gulf of Mexico.
- Applying a bias correction to all boundary variables excluding SST (BC\_NoSST, Fig. 5f) indicates the importance of getting the surface correct; the shear increases substantially and only 2 cyclones develop.

Longer period simulations for NO\_BC10 and BC10 produces similar results to those of the single season simulations (NO\_BC and BC), with ASO mean shear values over the North Atlantic too high for NO\_BC10, and realistic values being simulated for BC10 (Fig. 5g, h). These longer simulations also produce similar annual cyclone numbers to

those for single seasons:  $\sim 1.5$  for NO\_BC10 that developed too far north (Fig. 3a), and  $\sim 10$  for BC10 with much more realistic genesis locations and storm tracks (Fig. 3b).

Figure 6 shows the ASO Root Mean Square Error (RMSE) profiles of temperature, relative humidity, height and zonal wind for the MDR, using 20-year NNRP as a basis. Since the 20-year mean is being compared with a single season, the RMSE will reflect both the difference due to bias as well as interannual variability. In all cases the errors are reduced, as more boundary variables are bias corrected. This is especially notable in the upper-air. In general the NO\_BC case results in the highest RMSEs and the BC the lowest. The exception is height, where results are somewhat mixed. BC\_SSTUV also consistently performs well, although not as well as the BC case.

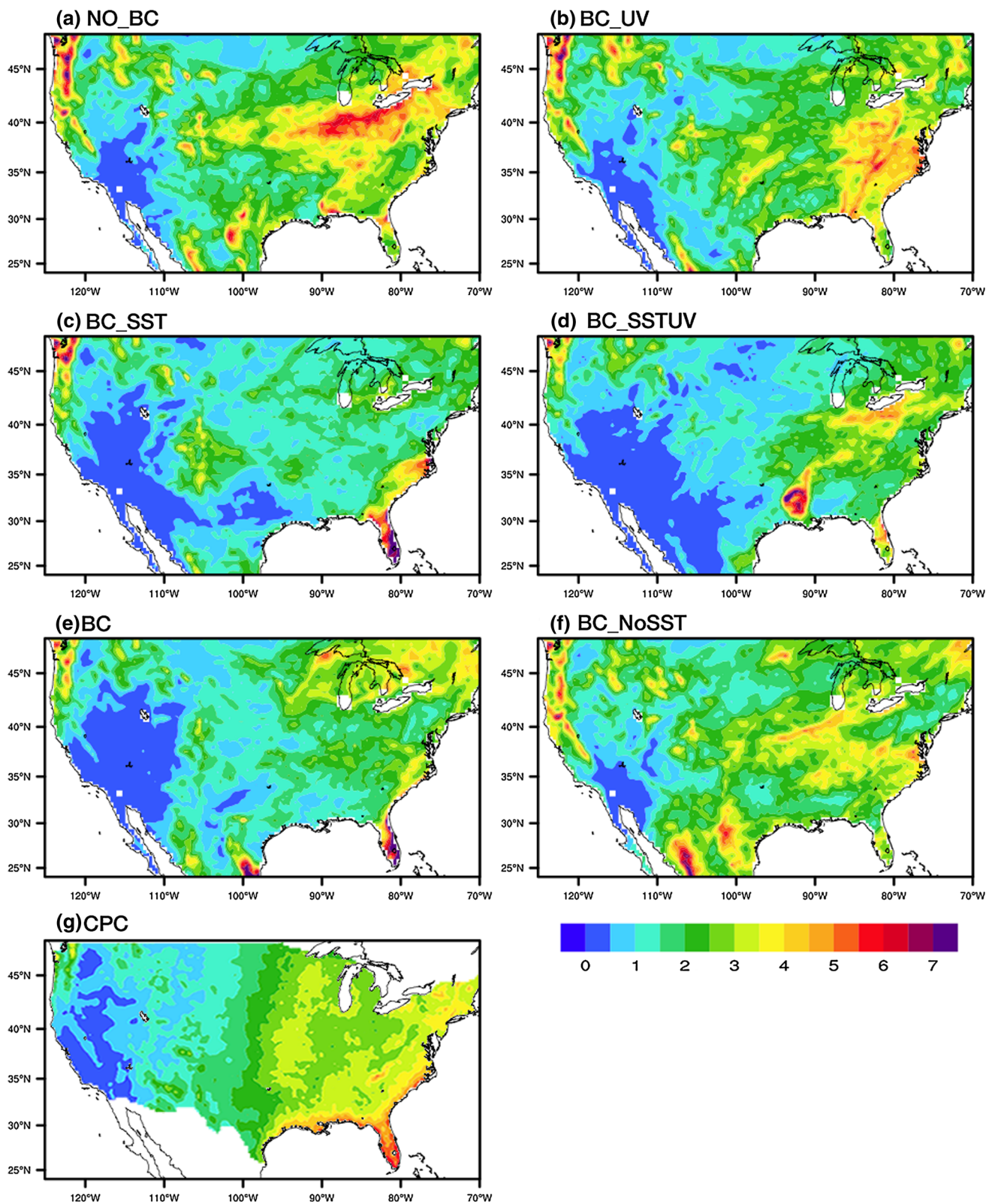
The Taylor diagram (Taylor 2001) in Fig. 7 provides an alternative measure of the performance of the various boundary modifications. There is a wide spread in overall response to different boundary modifications, and this depends on the variable that is chosen, with the upper-air values, which originally showed the biggest errors, responding most to the bias correction. The one clear signal is that applying all boundary modifications (BC, black dots) consistently produces the best results. Clearly, applying a consistent correction across all relevant variables provides the best outcome for dynamical downscaling with the NRCM.

### 3.2.2 North American summer precipitation and temperature

The impact of boundary bias corrections on summer precipitation over North America is shown by the ASO averages in Fig. 8a–f, which can be compared with the CPC Unified Gauge-Based Analysis of daily precipitation (Fig. 8g; data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at <http://www.esrl.noaa.gov/psd/>). A marked zonal gradient in the observed precipitation results from wet conditions along the east and Gulf coasts decreasing to generally dry conditions in the west. Although there is more noise due to the relatively short simulation periods, applying the full set of boundary conditions (BC, Fig. 8e) reproduces the observed pattern quite well. By comparison, using the raw boundaries (NO\_BC, Fig. 8a) produces a simulation that is far too wet in the central and northeastern USA. Here the correction for SST has the largest single influence, as can be seen by comparing Fig. 8a, b, f (*simulations without SST bias correction*) with 8c–e (*simulations with SST bias correction*). When all boundary corrections are made except for SST, the bias-corrected simulation is substantially degraded (Fig. 8f).

North American temperature simulations, although more robust than other variables, are also improved by the application of a bias correction at the boundaries (Fig. 9).

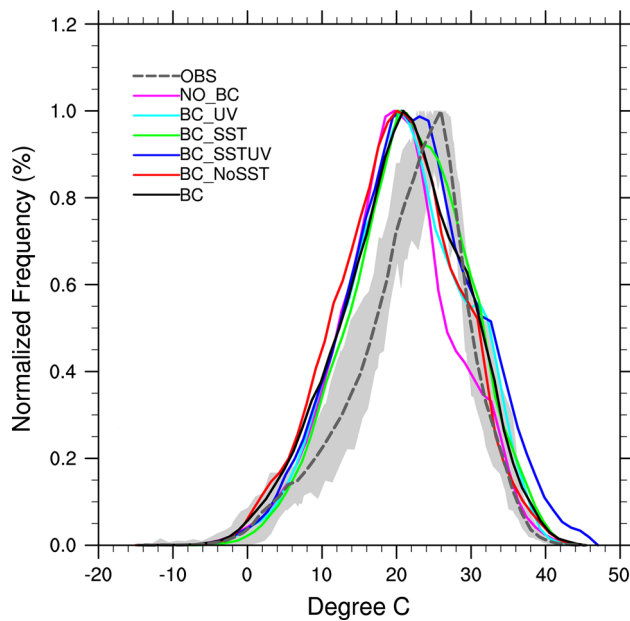




**Fig. 8** ASO-average daily precipitation (mm/day) for cases with bias correction applied to: **a** no variables (NO\_BC), **b** winds (BC\_UV), **c** SST (BC\_SST), **d** winds and SST (BC\_SSTUV), **e** all boundary

variables (BC), **f** all boundary variables excluding SST (BC\_NoSST), and, **g** 20-year ASO-average daily CPC Unified Gauge-Based Analysis of Daily Precipitation





**Fig. 9** Normalized distribution of ASO maximum daily surface temperature (2 m level) over the continental USA for observations and the six different sensitivity runs. The *dashed grey* line is the 20-year distribution of observed surface temperatures, with the *light grey shading* indicating the variance over the 20 observed years

Figure 9 depicts the normalized distribution of ASO maximum daily surface temperature (2 m level) over the continental USA for the 6 sensitivity runs (color lines), as well as the 20-year mean distribution from observations (dashed grey line). The light grey shading indicates the variance over the 20 observed years. The observed mean daily maximum surface temperature is around 23 °C, with the year-to-year variations from 21.5 to 23.5 °C. Applying raw boundary conditions results in a substantial regional cooling of 2–3 °C in the NRCM simulations compared to observations. Applying bias correction to specific variables or sets of variables improved this cold bias and, as with other experiments, using all boundary condition corrections together provided the greatest improvement.

#### 4 Conclusions

Biases in GCMs are transferred through lateral and lower boundary conditions to RCMs, impacting the downscaled results, sometimes severely. Here we examined application of a bias correction method that corrects the seasonally-adjusted mean error in the GCM but retains the weather variance, longer-period climate variability, and climate change from the GCM. The correction is nearly independent of the period over which it is developed, giving confidence that such corrections will be somewhat invariant in future projections. Corrections to both mean and

variance were considered, but the variance correction made very little difference, as the NRCM was able to successfully reproduce the observed variance internally.

The impact of both the full bias correction and individual components were examined in relation to simulations of the North Atlantic tropical cyclone environment and North American precipitation and temperatures.

A consistent result was achieved for all three components. Using the uncorrected climate model boundary conditions resulted in substantial errors, including suppressing almost all tropical cyclones. Applying the full correction to all boundary variables substantially improved the simulations compared to observations: simulated tropical cyclones had realistic spatial distributions and annual frequency; North American precipitation distribution and magnitude was substantially improved; and the probability distribution of surface temperatures moved from a distinct cold bias to a better approximation of observations.

Correcting individual and groups of boundary variables in isolation indicates that the biggest single improvement came through correcting the SST. Correcting both SST and winds at the horizontal boundary provided the majority of the improvement. But in all cases correcting all boundary variables in a consistent manner was better than correcting any subset of variables.

These findings suggest that application of a relatively simple bias correction to the GCM boundary conditions for a RCM—in which only seasonal variability is included—may suit many regional climate applications. A particular strength of this approach is that it enables current-climate variability within the GCM (weather, decadal and climate change) to vary with future simulations while correcting for the major biases that can cause serious issues for regional climate downscaling.

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